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A review of time use models of residential electricity demand

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ABSTRACT

Residential electricity demand in most European countries accounts for a major proportion of overall electricity consumption. The timing of residential electricity demand has significant impacts on carbon emissions and system costs. This paper reviews the data and methods used in time use studies in the context of residential electricity demand modelling. It highlights key issues which are likely to become more topical for research on the timing of electricity demand following the roll-out of smart metres.

Contents

1. Introduction

Residential electricity demand in most European countries accounts for a major proportion of overall electricity consumption. Traditionally, electricity metering at a residential level has been conducted at a low time resolution, either on a monthly or bi-monthly basis. Most policy-makers, energy suppliers and energy service companies base their policies, tariffs and projects based on average load profiles on daily or monthly basis. The recent and forthcoming high penetration of smart metering technologies in developed countries has increased the significance of time use data [1,2]. Time use data report activities carried out by people throughout the day [3]. They are becoming increasingly relevant for peak electricity demand issues. At what time residential end-users switch lights, heating and appliances on, for how long, and at what time they switch them off determines the individual electricity consumption profile in the household [4]. The sum of individual profiles in a neighbourhood or district determines the

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time-related electricity consumption of a specific section of the distribution network [5]. Peak loads in the transmission grid occur when on aggregate a vast amount of residential end-users is using electricity at the same time [6]. When this happens, typically in the late afternoon of a winter day, the costs and negative environmental impacts of meeting this extraordinarily high demand are higher than normal. This is because energy suppliers have to activate carbon intensive power plants to compensate for such increase in demand [7,8].

One question that scholars have been seeking to address for some time relates to how to measure the timing of residential electricity demand [9]. Various models have been deployed, from stochastic predictions of appliance use to weather-related deterministic models. One emerging approach consists of tracking people's practices in and out of the household, following the assumption that residential electricity demand is determined predominantly by the timing of human activities (e.g. travelling to work and taking children to school) [10]. This approach tends to rely on either measured time use survey data or synthetic stochastic models.

This paper reviews the data and methods used in time use studies in the context of residential electricity demand modelling. It reviews the literature on existing models for residential electricity demand in relation to the types of data they use (Section 2); describes modelling approaches used in time use studies (Section 3); reviews time use studies (Section 4); discusses some of the limits of time use approaches; and concludes by exploring how the research area of time use might evolve in the future (Section 5).

2. Data for modelling residential electricity consumption: a review of the literature

The literature on electricity demand makes use of different approaches to model the timing of residential electricity consumption. The approaches originate from different disciplines, including energy econometrics, electrical engineering, sociology of practice, environmental psychology and household economics. Traditionally, reviews of models of electricity consumption tend to focus either on the modelling method [11–13] or the discipline [14]. This review focuses on data with a view to critically examine existing datasets informing residential electricity demand and exploring the advantages and disadvantages of each approach in relation to the timing of residential electricity demand.

2.1. Models using actual or simulated end-use data

Electrical engineers use either actual or simulated end-use data to construct electricity consumption profiles. Average energy efficiency, average appliance power ratings and end-use features are typical examples of the type of input data required in electrical engineering models. The simulation component of this kind of modelling implies that residential electricity loads are forecasted even in the absence of historical data information on electricity use. Yao and Steemers [15] make use of a dynamic software model to generate load profiles of domestic space heating load for different types of dwellings based on occupancy patterns, appliance ratings and appliance ownership. Their study distinguishes between behavioural determinants of residential electricity consumption (which are associated with the weekly, daily or hourly basis when specific appliances are used) and physical determinants (which are associated with unchangeable variables like the size of the dwelling).

Shimoda et al. [16] construct residential electricity load profiles for different dwelling types and household features with a granularity of one-hour period. Their study, which is based in a urban setting in Japan, shows that occupants' time use, appliance efficiencies, external temperature and dwelling thermal characteristics affect residential electricity consumption profiles. Papadopoulos et al. [17] apply a simulation software to model residential energy use in Greek households and compare the economic and environmental performance of different typologies of space heating. Oil fired boilers underperform in comparison with heat pumps, electric radiators and gas fired boilers.

Higher granularity models for residential electricity profiles need to rely on both behavioural factors, including psychological and sociological consumption motives, but also demographic and socio-economic factors. For instance, McLoughlin et al. [18] analyse how total electricity consumption, maximum demand, load factor and time of use of maximum electricity demand relate to different dwelling and occupancy socio-economic variables. Time of use tariffs consist of differentiated electricity prices for distinct times of the day (i.e. peak and off-peak tariffs). They find that dwelling type, number of bedrooms, head of household age, household composition, social class, water heating and cooking type play a significant role over total residential electricity consumption. A strong relationship is in place between maximum demand and household appliances (i.e. tumble dryers, dishwashers and electric cookers).

The employment of end-use data has the merit of providing close to reality proxies to residential electricity demand without having to rely on historical consumption data. This means that in some cases the physical and behavioural data used as input in the model can be integrated with time use data, hence offering a break-down of residential electricity loads which can be useful to Transmission System Operators (to balance demand and supply near real time), Distribution Network Operators (to differentiate tariffs) and demand side participation aggregators (to offer demand side response services to residential customers). However, most of the models reviewed above can hardly be extended or generalised to wider population samples. As a result, models relying on either simulated or actual end-use data can be complex to validate and implement.

2.2. Models using macroeconomic data

Energy econometricians use aggregate macroeconomic data (e.g. GDP, average income levels, population size, national energy prices) in order to correlate electricity demand profiles with socio-economics variables.

O'Doherty et al. [19] apply the Papke–Wooldridge generalised linear model from the Irish National Survey of Housing Quality. By exploring the relationship between electricity consumption and appliance ownership, they find out that dwelling characteristics, location, value, dwelling type, occupant characteristics, income, age, period of residency, social class and tenure type play an important role in explaining residential electricity consumption. Filippini and Hunt [20] rely on the framework of household production theory to model residential electricity demand as an input to the demand function. Their model controls for income, price, population, average household size, heating degree days, cooling degree days and the share of detached housing to assess residential "underlying energy efficiency". Other studies use time series to assess the degree of correlation between residential electricity demand, on the one hand, and, on the other hand, household total final consumption expenditure, real energy prices and underlying energy demand [21–23].

Parti and Parti [24] make use of survey data on appliances and electrical billing data when developing their conditional demand analysis model. Because of their attempt to determine the use level of individual appliances based on regression methods, the behavioural data inputting into their model are highly theoretical

and not based on empirical grounds. Chitnis et al. [25] infer that in the UK expenditure in electricity may not raise up to 2030 based on assumptions for real household disposable income and real prices and "exogenous non-economic factors". The analysis of patterns of electricity consumption in relation to dwelling type, floor area, number of occupants, number of bedrooms, tenure, occupant age and household income in Yohanis et al. [26] shows that floor area is the most significant factor.

Models using macroeconomic data are particularly useful when they are based on large dataset. However, such models are often faced with issues of multi-collinearity between variables. They also tend to be resource-intensive and lengthy. Attempts to combine aggregate macroeconomic data with disaggregate load profile data have encountered problems because of the multicollinearity effects which can result in negative or unreasonable coefficients. For instance, Aigner et al. [27] find that while the magnitude of coefficients indicating end-use consumption changes throughout the day with load level, the relationship between different appliances does not change. This means that coefficients characterising average end-use level and are not representative of the daily use electricity load.

2.3. Models using price data

Price is knows for affecting electricity demand both in terms of aggregate consumption and disaggregate load profiles. On the one hand, studies analysing the extent to which aggregate residential electricity consumption profiles are shaped by changes in flat tariff prices typically rely on price information from bills [28]. On the other hand, models examining short-term elasticities (i.e. how loads change based on short-term variations in price) frequently rely on metered data. According to these approaches, the success of a tariff is based on the price elasticity of demand [29]. Given the statistical properties of aggregate data on residential users' expenditure and variations in price, this formulation would yield a robust dynamic empirical inverse relationship between consumption and changes in price. Several studies investigated this known relationship [30–35]. The major problem which emerged in empirical research based on this hypothesis has arisen in fitting the part of the model that relates current and past observed income to expected future changes in prices [36,37].

2.4. Models using physical non end-use data

Models using primarily physical non end-use data mainly rely either on external temperature data or daylight data. Studies looking at external temperature data generally find a significant relationship between electricity end-uses and external temperature [38–40], although a methodological bias might occur because existing studies are more representative of hot climates than temperate climates. Hill et al. [41] use Support Vector Regression to estimate electricity demand on a half-hourly basis with a view to assess the energy and costs savings associated with the change in time if the UK were to maintain daylight savings time over winter, instead of reverting to Greenwich mean time.

Biological data are used in networks models to simulate electricity consumption in residential buildings. Traditionally, the data originate from electric utility forecasts with the integration of input parameters which have an impact on residential electricity consumption. Input data are typically appliance ownership, appliance use, household income, type of dwelling and number of occupants [42]. Neural network models frequently present problems in terms of multi-collinearity due to possible high levels of appliance saturation.

Based on the studies reviewed in this section, Fig. 1 illustrates which data types are used more frequently when modelling residential electricity demand. The frequency of data use is given by the number of citations in peer-reviewed journals.

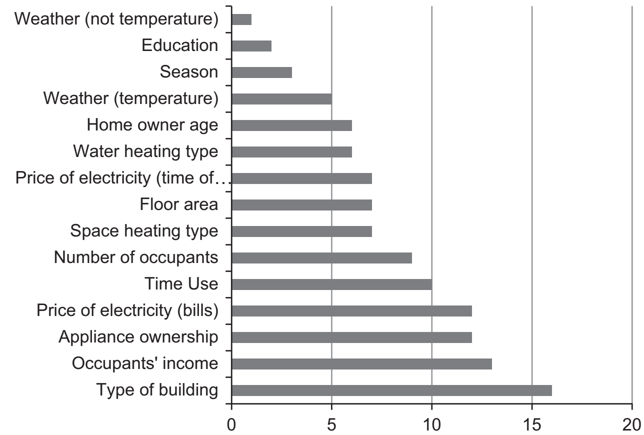

Fig. 1. Data used in residential electricity demand models: number of citations.

Fig. 1 shows that type of building, occupants' income, appliance ownership and bill-related price of electricity are some of the most used data in models for residential electricity demand. Time use data have been employed 10 times in the reviewed studies. It should be clarified that higher frequency of data use is not necessarily related to the performance of the dara, but also to the analytical framework of the study and the extent to which one data type can be either related to or combined with other types of data within the models.

Fig. 2 shows an example of time use data for electricity demand use as part of the DEMAND initiative (www.demand.ac.uk).

3. Modelling residential electricity demand based on time use data

Time use is along with weather [43,44], building characteristics [45,46], lifestyle of occupants [47–49], habits of occupants [50–52], appliance design [53–56] appliance control [57] and interdependencies between energy services [58] a crucial variable for defining energy consumption. It is arguably the most important variable for explaining the timing of energy demand in the household. Even those researchers who have used other variables to model energy demand acknowledge the importance of occupancy. For instance, according to Yao and Steemers [15], "the load profile depends very much on the occupancy pattern". This opinion is share by Stokes et al. [59]: "Taking account of occupancy patterns would improve the modelling of diversity."

Although the number of studies explicitly linking demand profiles with time use data is limited, much can be learned from them and from those studies which attempted to model the timing of residential electricity demand from time use data. Residential electricity demand profiles are highly correlated with timing of active occupancy, i.e. when consumers are at home and awake. One of the most common approaches consist of simulating time use using probability, stochastic modelling and applications of the Markov-Chain technique. Other approaches involve developing demand profiles based on existing time use data from surveys methods.

3.1. The Markov chain technique

The Markov chain technique determines how likely it is that a household's electricity demand at a certain time of the day corresponds to a certain load. It generates electricity consumption

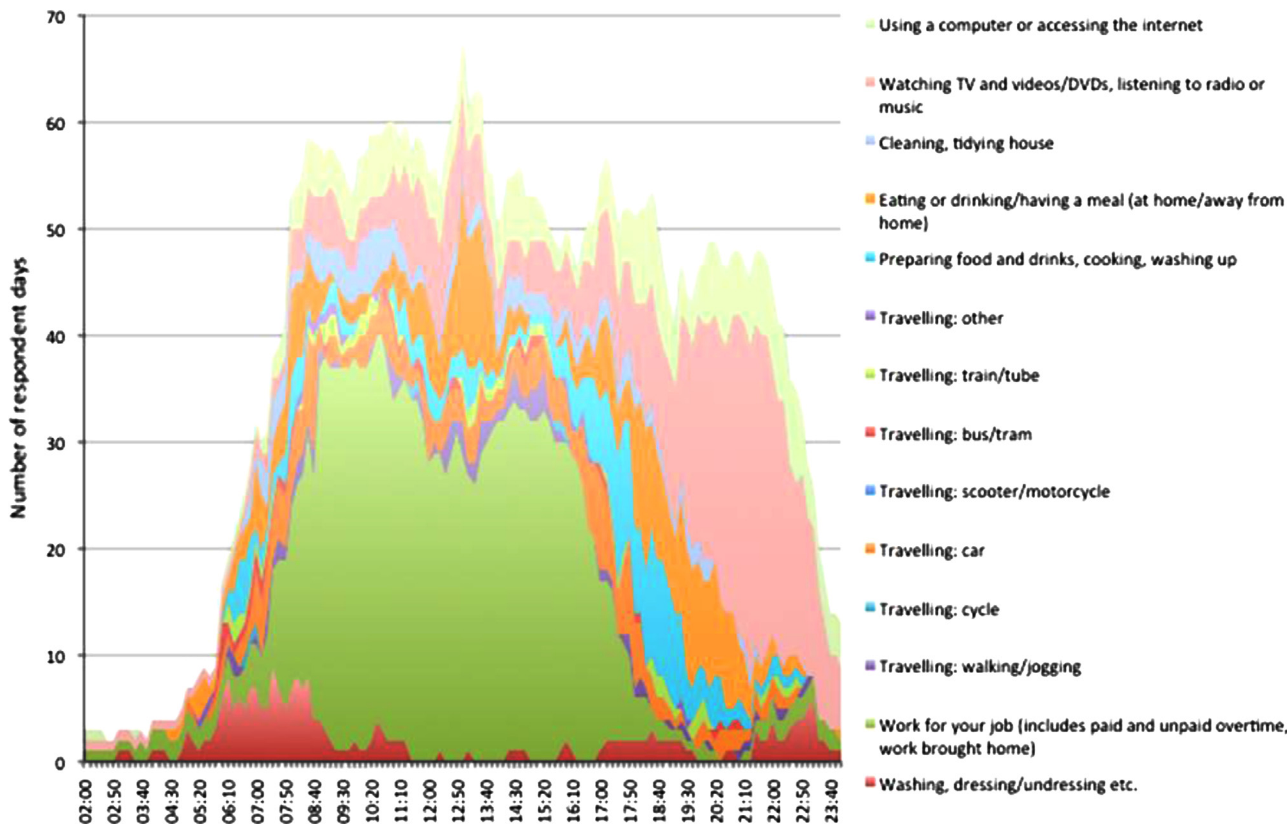

Fig. 2. Example of time use data application from trajectory dataset.

Table 1
Example of diary entry in national time use surveys.

Diary/person id	Starting time	Ending time	Main activity	Parallel activity	Who with:				Where/mode of tranport
					Alone	Spouse	Small child	Other pers.	
AA23	04:00	07:20	Sleep						At home
AA23	07:20	07:50	Shower						At home
AA23	7:50	08:30	Had breakfast	Read newspaper			Ch		At home
AA23	08:30	08:40	Walked to bus		A				By foot
AA23	08:40	09:00	Bus to job					OP	By bus

profiles through a stochastic process making use of probability distributions in a similar way as Monte Carlo analysis.

Formally, a Markov chain is a collection of random variables with the property that, given the present, the future is conditionally independent of the past [43]. This means that the Markov chain of random variables x_n associated with discrete values $\alpha_1, \ldots, \alpha_N$ can be represented as

$$P(x_n = \alpha_{in} | x_{n-1} = \alpha_{in-1}, \ldots, x_1 - \alpha_{i1}) = P(x_n = \alpha_{in} | x_{n-1} = \alpha_{in-1}).$$

Markov chain modelling is based on the development of a transitional probability matrix where the transition from one discrete state to another discrete state is represented in terms of its probability. A first order Markov chain model takes into account the current state and the previous state to estimate the probability of going to the subsequent state. A second order Markov chain model considers the two preceding states and compares them with the current state to determine the next state.

The transition probabilities vary with time to reproduce day-time variations. For instance, the probability of changing from active occupancy passive occupancy typically increases after 10 PM. The transition probabilities are non-homogenous, meaning that they are not fixed. For a single occupant, an assumption is made regarding her/his initial condition. Subsequently, a uniform random number is generated for each transition probability from one time period to the next. The Markov chain technique is suited to modelling systems where the current state of a sequence is highly correlated to the state immediately preceding it and where a large sample size of data exists. It is an autoregressive process which can generate synthetic sequences for modelling stochastic residential electricity consumption as well as weather conditions, e.g. wind speed and rain precipitation.

3.2. Using measured time use data

The timing of human activities can be traced in various ways, including ethnographic studies, questionnaires, and GPS methods. The most comprehensive information about the timing of human activities is given by national time use surveys. In national time use surveys, the data collection takes place by means of time diaries covering 24 h. Respondents are asked to fill in diaries for one or two randomly designated days, stating what activities were performed, where they were performed and with whom. An example of diary data entry is shown in Table 1.

Table 2
Human activities in Belgium between 4.00 AM and 6.00 AM (from HArmonised European time use survey dataset).

Country	Starttime	Work and study	Travel to/from work/study	Household work	Sleep and other personal care	Eating	Freetime	TV and video	Unspecified time
Belgium	04:00	1.04	0.07	0.16	97.16	0.15	1.01	0.17	0.24
Belgium	04:10	1.09	0.09	0.28	97.14	0.18	0.85	0.14	0.23
Belgium	04:20	1.09	0.15	0.18	96.94	0.4	0.81	0.17	0.25
Belgium	04:30	1.13	0.35	0.23	96.51	0.27	1.09	0.17	0.27
Belgium	04:40	1.23	0.34	0.36	96.46	0.2	0.97	0.15	0.29
Belgium	04:50	1.26	0.35	0.44	95.81	0.49	1.16	0.18	0.31
Belgium	05:00	1.53	0.34	0.61	94.76	0.49	1.78	0.21	0.27
Belgium	05:10	1.6	0.47	0.68	94.82	0.61	1.34	0.21	0.27
Belgium	05:20	1.71	0.64	0.61	94.54	0.65	1.25	0.24	0.36
Belgium	05:30	1.83	0.95	0.7	93.31	0.77	1.84	0.22	0.37
Belgium	05:40	1.94	1.26	0.99	92.77	0.74	1.74	0.24	0.3
Belgium	05:50	2.31	1.22	1.08	91.76	0.98	2.09	0.21	0.36
Belgium	06:00	3.08	1.06	1.39	88.08	1	4.81	0.23	0.34

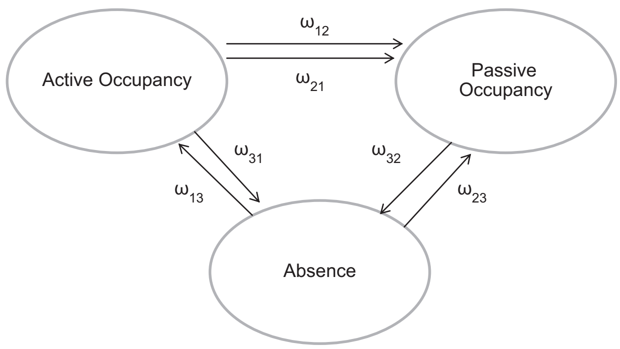

Fig. 3. Variations in types of occupancy based on time use survey data.

The results of national time use surveys are summarised in 10-minute intervals. This way it is possible to know, for instance, how many people are showering between 7.20 and 7.30 on a typical weekday. The aggregation of all diary entries gives a statistically significant indication of the timing of human activities of children and adults in a single country. What is more, the level of aggregation can be even higher and take into account the timing of human activities of a whole continent (in Europe the Harmonised European Time Use Survey consists of 220,464 comparable individuals across 15 countries). Table 2 shows an excerpt of the Harmonised European Time Use Survey dataset. Unsurprisingly between 5.00 AM and 5.10 AM 94% of Belgians is sleeping.

Time use surveys specify the timing of some activities taking place outside the household, e.g. travelling by public transport. Other activities outside the household are difficult to reconcile with the timing of electricity consumption – for instance "being at work" does not link this activity with electricity demand. For activities inside the household, the extent to which appliance-specific data can be reconciled with residential electricity demand is strictly related to the level of disaggregation of the time use data. This mainly depends on how appliance-specific the diary entry is.

For instance, for the entry called "TV and Video watching" it is possible not only to derive the timing of electricity demand, but also, with some approximation about the average efficiency ratings of the TV and video sets, the actual physical demand in KWh. However, diary entries like "household work" are not appliance specific, making it difficult to associate the timing of that activity with electricity demand.

Fig. 3 shows the changes in types of occupancy which take place between time intervals, where $\omega_{\mathrm{t,t+1}}$ is the level of occupancy between the time t and the time $t+1$. The segmentation of the time use data in terms of number of occupants can simplify the assessment of the variations in occupancy.

Three indicators of how much occupancy varies from one time period to the next are simple occupancy variation, cumulative occupancy variation and occupancy variance. For single person households, the variation in occupancy is given by

$$\Delta(t, t+1) = \omega_{\mathrm{t+1}} - \omega_{\mathrm{t}};$$

the cumulative occupancy variation is

$$\phi = \sum_{t=1}^{N} |\Delta_{t,t+1}|$$

and occupancy variance is

$$\beta_{t,t+1} = \omega_t / \omega_{t+1}$$

Households with high occupancy variance are associated with high variability in loads throughout the day. Viceversa, households with a low variance might be receptive of load variations.

4. Review of residential electricity demand models based on time use data

Two seminal studies lay the foundations for residential electricity demand models based on time use data. Firstly, Wood and Newborough [56] use three characteristic groups to explain electricity consumption patterns in the household: "predictable", "moderately predictable" and "unpredictable". Predictable loads consist of limited cyclic loads taking place at a time of passive occupancy. Moderately predictable relate to the habitual behaviour of occupants. Unpredictable loads describe the vast majority of electricity consumption within a dwelling. Predictable loads follow a deterministic approach, whereas unpredictable loads may be seen as following a stochastic approach. Secondly, Firth et al. [60] analyse groups of electrical appliances (continuous and standby, cold appliances and active appliances) in terms of time of the day when they are likely to be switched on. The authors distinguish between deterministic and stochastic timing of appliance use. For example, electricity consumption from appliances like kettles and electric showers are significantly arbitrary and are typically associated with high electric load requirements.

Stokes et al. [59] model domestic lighting with a stochastic approach, generating load profiles with a resolution of 1 min from the 30 min resolution of measured data in 100 households. Capasso et al. [61] model 15-min period consumption patterns based on appliance and homeowner variables. Their work demonstrates that behaviour-related usage and income-related appliance ratings play a significant role in explaining load patterns.

Richardson et al. [62] develop a bottom-up occupancy model for UK electricity demand starting from the UK Time Use Survey. The model generates active occupancy data for UK households

Table 3
Review of time use studies.

	Number of dwellings (simulation)	Persons (from time use surveys)	Country	Duration	Period	Approach	Time resolution (in min)
[61]	95 (4 buildings)	40,000	Italy	1 year	1/6/1988–31/5/1989	Montecarlo analysis	15
[67]	5		Ireland	6 months	1/7/2009–31/12/2009	Markov chain compared with measured data	30
[62]	50	9991	UK	1 year	2000	Markov chain compared with measured data	10
[63]	22	9991	UK	1 year	2000	Markov chain compared with measured data	10
[59]	100	–	UK	1 year	1/3/1996–30/4/1997	Stochastic approach to model residential light demand	1
[68]	–	73,215	EU15	1 year	1991–1006	Estimating occupancy variances	10
[66]	217	3980	Sweden	1 year	1996 and 2007	Markov chain to model residential hot water demand	5
[65]	14	3980	Sweden	1 year	1996 and 2007	Markov chain to model residential light demand	10
[53]	169	3980	Sweden	1 year	1996 and 2007	Markov chain compared with measured data	1
[77]	20	15,441	France	1 year	1998–1999	Markov chain used to calculate probabilities of different activities	10
[78,79]	–	9541	Spain	1 year	2009–2010	Estimating occupancy variances	10

based upon surveyed time use data describing what people do and when. It makes use of a probabilistic approach to infer how many other occupants enter or leave the household between a 10 min interval and the next one. Additional applications of occupancy profiles in demand modelling could make modelled data depend on the availability of occupants. The generation of occupancy data is used by Richardson et al. [63] as a starting point for their electricity demand simulation, which covers major household appliances. In this case, the Markov chain technique, is validated by actual data from electricity users.

Similarly, the model by Widén and Wäckelgård [64] simulates household activities based on time use data in Sweden. The timing of electricity demand is derived from occupancy patterns along with appliance holdings, ratings and daylight distribution. The household activity simulation is produced on the basis of non-homogeneous Markov chains which reduce occupancy data set to 1 min intervals. Similar applications relate to residential electricity profiles in association with lighting [65] and water heating [66]. The positive research experience by Widén and co-authors in applying Markov chains is not shared Duffy et al. [67]. They apply the Markov chain model to five different dwelling types over half hourly intervals using a 24 by 24 probability matrix. They compare Markov chain synthetically generated load profiles with metered electricity consumption. While most descriptive statistical values, including mean, standard deviation, maximum and minimum values are satisfactory transferred between simulated and actual data, the temporal properties of the Markov chain performed inadequately compared with the metered load profiles. In other words, their findings show unusual peak loads during the day and night which do not correspond to existing load profiles.

Torriti [68] develops a Europe-wide model of occupancy to identify occupancy peaks in 15 European countries. He constructs Europe-wide occupancy profiles based on the Harmonised European Time Use Survey. He makes use of the TV, DVD and video watching activity to assess the peak load of such activity between 8.20 PM and 8.30 PM. Some of the problems with multiple occupancy and Markov chain stochastic modelling are obviated by filtering the Harmonised European Time Use Survey data with single-person households only.

Widén et al. [66] shows that time use data can be used for highly realistic descriptions of behavioural factors associated with energy demand. Time use data are used to describe occupancy patterns in a stochastic Markov chain based model of domestic lighting demand [65]. Page et al. [69] develop a comparable stochastic model to simulate occupancy. Paatero and Lund [70] discuss some of the problems with gathering realistic time use data and aggregating individual appliance loads, over a time-series and benefit from "grassroot level consumption details", or detail on "statistical averages" in order to configure the model. Time use trends can also be used to feed into models for lighting [71] and ventilation [72].

Wilke et al. [73] model household activities based on time-dependent probabilities about when the activities are likely to start and their corresponding duration distributions. Their model is informed by French Time Use data from 1998 to 1999. Transitions between successive activities were modelled based on the first-order inhomogeneous Markov property.

Table 3 summarises the reviewed studies making use of national time use data and probability modelling. Measured data have been repeatedly used as inputs to Markov Chain models and, less frequently, for validating synthetic data. The majority of studies make use of 10-min interval data. This is supposed to have high applicability for demand side response purposes. For instance, demand side response programmes in California making use of ancillary services consist of reductions in the underlying load within periods of 10 min. In Finland, synchronised reserve programmes enable load removal from the system within 10 min of the request from the Independent System Operator dispatcher due to electrically synchronised smart metering equipment [68].

5. Conclusion

5.1. Limits of time use studies

The reviewed studies show that there are at least six issues which impact the measurement of the timing of residential electricity demand through time use data.

First, time use data are not significant for individual users. Their statistical significance increases with higher numbers of aggregate users. For this reason large datasets (like the national time use surveys) are more significant than detailed individual user ethnographic data on e.g. causal relations for particular timing of activities. For example, Duffy et al. [59] find validation of Markov chains difficult given the limited sample (5 dwellings) and time coverage of their study (6 months).

Second, time use data are representative of average days, typically weekdays, where societal constraints standardise routine and practice of everyday life. However, some of the most sizeable peak events take place on non-average days due to either particular weather conditions – e.g. a very cold winter day in Northern Europe or a very hot summer day in North America,

where the use of air conditioning is diffused [74] or rare public events – e.g. a football final or a royal wedding. This has significant implications on the study of aggregate peak electricity loads.

Third, nation-wide time use surveys are conducted very seldom. The last UK time use survey was carried out in the year 2000. The last time use survey in Europe at the time of this paper was the 2009 Spanish Time Use Survey. Whilst most occupancy and mobility patterns may not have changed dramatically, the evolution in the use of electronic devices calls for a careful consideration of "old" time use data in relation to "new" timing of residential electricity demand.

Fourth, the comparison of time use profiles among national datasets emphasises high similarities [68]. These could be explained through globalisation or other reasons. Regardless of what the explanations for such phenomenon might be, the high level of similarity in occupancy patterns demonstrates that, at least in developed countries, the timing of occupancy is less variable than other factors that influence energy consumption (e.g. weather, appliance design, etc.). This partly explains what energy econometricians define as the rigidity of the residential demand curve against time and price.

Fifth, whilst occupancy for single-person households is relatively easy to forecast, for multiple-person households the flow inside and outside the household is much more difficult to model. The experiences by Richardson et al. [62,63] and Widén et al. [64–66] demonstrate that attempts to model every other occupant stochastically have the merit of being comprehensive at the expense of undermining the comparability between metered and synthetic data.

5.2. Future time use research on residential electricity demand

Time use research modelling residential electricity demand modelling has experienced fairly recent developments and is likely to expand. The creation of data time series is still confronted with the challenge of expanding existing input time-use datasets. In principle, it is possible to expand time series given historical daily patterns in series, with a view to rely less on input data and more on synthetic data. However, as observed in the previous section, the level of aggregation and a close scrutiny of the social practices in the household are the only – seldom available – ways to avoid substantial assumptions. Given the relative infrequency of nationally significant time use surveys, the integration of social practice theory and case study data on appliance use in the household with time use data can be seen as a way forward in this area.

Another future development could consist of improving the generation of synthetic data by preserving the important diurnal variations in the time use data and limiting the amount of input data to the number of transition probabilities of the Markov chain [65]. Alternative variations of the Markov chains could combine Montecarlo analysis probabilities with other factor values. This review has attempted to extrapolate which data in the literature on modelling residential electricity demand have higher compatibility with time use data – both metered and simulated.

Studies confronting synthetic data (e.g. from Markov chain modelling) with actual data will increasingly be confronted with some of the inaccuracies of metered load profiles. The same modelling techniques might find useful applications in supplying occupancy-level information where there are gaps in data panels. Already, some of the existing studies have provided higher resolution for specific energy demand services, e.g. lighting [59,65].

Secondary data on time use activities and data generated by probabilistic models, e.g. Markov chains, may find practical implementations in visualisation projects. For instance, VISUAL-TimePAcTS is a visual analysis tool which has been developed for displaying and interacting with time use data. The tool gives a visualised image of the time and location of a different set of time use activities in relation to the energy consumption of the technologies or appliances used by individuals.

5.3. Metered data and synthetic data

This review looked at past research models focusing on time use data. With regards to the future of research on the timing use of electricity demand, much will change with the introduction of In Home Displays (or "smart metres") in every home, which is going to multiply exponentially measured data.

Thus far, In Home Displays have been rolled out only in a limited number of countries. In 2010 the only European countries with double-digit percentages of implementation of smart metres vis-à-vis total electricity metres were Sweden (98%), Italy (93%), Finland (19%) and Denmark (13%) [75]. However, the recent plan to roll-out smart metres in the UK (and other European countries) up to 2019 will trigger monitoring studies aimed at detecting the electricity consumption of individual households via advanced metering technologies and thus deriving aggregate consumption at national (and European level). At the time of writing this paper, In Home Displays had just accessed the market and pilot trials had been conducted in the UK and other European countries countries for measuring time-related performance of residential, commercial and industrial consumers. Compared with energy models based on time use data, the monitoring studies will rely on metered data from two-way communication systems to record consumption at different times of the day [76].

The introduction of monitoring studies based on actual smart metering data will be the acid test for future research on time use. On the one hand, future research may retrospectively look at energy models based on time use data with the dual purpose of estimating the error between time use curves and residential load profile curves and evaluating *ex post* the accuracy of such models. On the other hand, other research may make use of the validation between metered data and models with a view to build integrated approaches to forecasting residential electricity demand.

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